A Deep Learning Based Rotten Food Recognition App for Older Adults: Development and Usability Study

Minki Chun, Ha-Jin Yu, Hyunggu Jung

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Minki Chun[1] MS; Ha-Jin Yu[1] PhD; Hyunggu Jung[1] PhD

[1]University of Seoul Seoul KR

Corresponding Author:
Hyunggu Jung PhD
University of Seoul
Rm 207, Information and Technology Building
163 Seoulsiripdae-ro, Dongdaemun-gu
Seoul
KR

Abstract

Background: Older adults are at greater risk of eating rotten fruits and of suffering food poisoning because cognitive function declines as they age, making it difficult to distinguish rotten fruits. To address this problem, researchers have developed and evaluated a tool detecting rotten food items in various ways. Nevertheless, little is known about how to create such an app to detect rotten food items to support older adults in danger of suffering from health problems from eating rotten food items.

Objective: This study aims (1) to create a smartphone app that enables older adults to take a picture of food items with a camera and classifies whether the fruit is rotten or not for older adults, and (2) to evaluate the usability of the app and their perceptions of older adults about the app.

Methods: We developed a smartphone app that supports older adults in determining whether the fruits are fresh enough to eat. We used several residual deep networks to check whether the collected fruit photos were fresh fruit. We recruited healthy older adults aged over 65 years (15 males and 11 females) as participants. Then, we evaluated the usability of the app and perceptions of older adults with the app through surveys and interviews. We analyzed survey responses, including an after-scenario questionnaire, as evaluation indicators of the usability of the app and collected qualitative data from interviewees for in-depth analysis of survey responses.

Results: The results of this study showed that healthy older adults were satisfied with using an app that determines whether the fruit is fresh by taking a picture of the fruit but would be reluctant to use the paid app. The survey results revealed that participants tended to use the app efficiently to take pictures and determine the freshness of fruits. The qualitative data analysis revealed several categories, such as usability of the app and their perceptions about apps.

Conclusions: This study suggests the possibility of developing an app that supports older adults in identifying rotten food items effectively and efficiently. Future work still remains to make the app distinguish the freshness of various food items other than the three kinds of fruits.

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Keywords: digital health; mobile health; smartphone; classification; app; digital sensor; classification; deep learning; aging

Introduction

Older adults over the age of 65 need a system that supports distinguishing rotten food items because older adults are exposed to the danger of eating rotten food and suffer from health problems [1]. Older adults have a lower ability to recognize whether food item is rotten than other age groups [2], and as they get older, their cognitive function decreases [3], which causes an overall decrease in proportion to the visual, olfactory, and gustatory functions [4].

Prior studies found that decreased olfactory functions increases the chances of eating rotten foods. According to a study by the University of Pennsylvania Medical School, olfactory disorders affect the quality of life, appetite, and weight [5]. Similarly, the results of the National Health and Nutrition Examination Survey in the United States found that people over the age of 70 have difficulty recognizing dangerous odors such as smoke and gas [6]. As such, older adults are in danger of being exposed to food poisoning if they ingest rotten food items due to the difficulty in detecting it. Food poisoning is caused by the ingestion of toxic substances as well as bacteria contained in rotten food items [7]. In order to address this danger, researchers developed and evaluated a tool that detects rotten food items [8-9]. A tool for detecting rotten food items is used for unspecified users or specific users, such as people with olfactory impairment. Prior studies used chemical sensors and kits to detect rotten food items and measure freshness and, in some cases, cameras [10].

Rotten Food Items Detecting Tools Targeted at Unspecific Users

Prior studies proposed and evaluated tools to measure freshness for unspecified users [11-24]. Researchers used chemical sensors or kits to detect the spoilage in specific food items such as pork and chicken [11-14] or unspecified food items [15-17]. Some researchers used chemical sensors [11-13] and kits [14]. They used chemical sensors to distinguish rotten food items such as ham [11], fruits (e.g., banana, grape) [12], and pork [13]. Specifically, Choi et al. [9 proposed a tool that determines whether the ham is rotten using a sensor that responds to sulfur-containing compounds in the gas generated during ham decay to detect the spoilage of ham produced in Spain. In addition, Caya et al. [12] proposed a tool for detecting gas generated during the decay of bananas, carrots, and grapes using an electronic nose and detecting decay using k-nearest neighbors and principal component analysis of the collected data. Similarly, Tian et al. [13] proposed a tool to detect spoilage in pork by detecting the number of aerobic bacteria in pork through a sensor and principal component analysis. Meanwhile, Mikš-Krajnik et al. [14] proposed a tool for detecting spoilage by detecting 27 kinds of volatile organic compounds generated during the decay of chickens and selecting three types of indicators highly correlated with spoilage to detect spoilage of chickens. On the other hand, other researchers proposed a tool for detecting spoilage of unspecified food items using chemical sensors [16, 17] or kits [15]. For instance, researchers proposed a tool for detecting decay using gas generated from meat, fruits, and vegetables using an electronic nose [16, 17]. Meanwhile, Janagama et al. [15] used an organism detection kit called a dipstick to detect wine spoilage.

On the contrary, researchers proposed various methods (e.g., convolutional neural network, Fourier transform infrared spectroscopy) to detect the spoilage of a specific food item using a camera [18-24]. Perez-Daniel et al. [18] used a camera to detect the spoilage of unspecific food items. They proposed a tool to detect spoilage through a neural network using RetinaNet by collecting images of normal food items and rotten food items, respectively, was also proposed to detect the spoilage of unspecified food. Other researchers proposed a tool to detect the spoilage of certain food items such as fruits [19-21], vegetables [22], beef [23], and rice [24]. For example, Karakaya et al. [19] obtained a co-occurrence matrix from a gray-scale histogram of an image to detect the decay of apples, bananas, and oranges and extracted features from the obtained matrix using the bag of feature method. The extracted features were classified into normal food items and rotten food items using a convolutional neural network and a support vector machine. In addition, researchers proposed a tool for detecting the decay of fruits [20] and citrus fruits [21] using visual features. Similarly, Jagtap et al. [22] proposed a tool for taking pictures of potatoes moving through a conveyor belt and detecting the decay of potatoes using a neural network and features extracted from the pictures has been proposed. Meanwhile, Ellis et al. [23] used Fourier transform infrared spectroscopy to detect food spoilage, which the researchers used to detect chemical changes in beef, and a tool to detect spoilage in beef using machine learning. Additionally, a tool for detecting the decay of Philippine rice using both a chemical sensor and a camera has been proposed, and it classified the data collected using the chemical sensor and camera into spoiled rice and normal rice using machine learning [24].

Rotten Food Items Detecting Tools Targeted at Specific Users

Prior studies proposed and evaluated tools to measure freshness for specific users, such as people who manage the freshness of meats [25-29]. These tools detect the spoilage of specific food items using chemical sensors or kits [26-28] or even the spoilage of unspecified food items [25]. Specifically, researchers proposed and evaluated a tool to determine the spoilage of tomato dishes [27], fish and beef [27], and milk [28] using a gas sensor. Researchers who proposed and evaluated a tool to detect spoilage of tomato dishes in the Philippines using an electronic nose for people with an olfactory impairment are using an electronic nose equipped with an MQ gas sensor and temperature and humidity sensors to reduce the spoilage of tomato dishes [26]. Similarly, a tool for identifying spoilage of fish and beef using an electronic nose, artificial neural network, support vector machine, and k-nearest neighbor method has been proposed for food freshness inspection in butchers [27]. Another study proposed a tool for identifying spoiled milk using an electronic nose and fuzzy c-means clustering to prevent older adults suffering from olfactory disorders and dementia from drinking spoiled milk [28]. On the other hand, Musa et al. [25] proposed a film that changes color when it encounters rotten food items by sensing the pH with corn starch-glycerol and anthocyanin for packaging material developers.

Meanwhile, a previous study proposed a tool for certain users to use a chemical sensor and a camera to determine food spoilage. Kodogiannis et al. [29] proposed a tool that detects microorganisms in meat using the Fourier transform infrared spectroscopy and an advanced clustering-based neuro-fuzzy identification model, determining the degree of meat spoil.

Limitations of Prior Studies

Nevertheless, little is known about studies that developed and evaluated apps to help determine the freshness of fruits for a basic diet of physically healthy older adults. Therefore, we developed and evaluated a smartphone app that classifies whether apples, bananas, and oranges are rotten or not for healthy older adults. Apples, bananas, and oranges are among the most consumed traditional fruits in South Korea and the United States [30]. At the same time, we could easily collect photos of rotten apples, bananas, and oranges, so we selected them as the target fruits of our app [31]. Textbox 1 shows the research questions of our study.

Textbox 1. The research questions.

- Research Question 1. What studies have previously evaluated and developed an app for healthy older adults by taking pictures of food items with a smartphone camera to classify whether the food items are rotten or not?
- Research Question 2. Is it possible to make an app that classifies apples, bananas, and oranges with only pictures of apples, bananas, and oranges taken with a

smartphone camera?
- Research Question 2-1. How can we gather the pictures that are needed to create a function for classifying apples, bananas, and oranges?
- Research Question 2-2. How can we create a function to classify apples, bananas, and oranges whether they are rotten or not?
- Research Question 2-3. How can we create an app that can use the function above?

■ Research Question 3. Is there a significant performance difference between functions created by various methods of classifying apples, bananas, and oranges?

■ Research Question 4. Is an app that classifies whether an apple, banana, or orange is rotten or not only by pictures taken using a smartphone camera easy to use?
- Research Question 4-1. Why are older adults satisfied with the task?
- Research Question 4-2. Why are older adults not satisfied with the task?
- Research Question 4-3. Why are older adults satisfied with the time it takes to complete the task?
- Research Question 4-4. Why are older adults dissatisfied with the time taken to complete the task?
- Research Question 4-5. What made older adults satisfied using the app?
- Research Question 4-6. What made older adults dissatisfied with using the app?
- Research Question 4-7. What do older adults want from using the app?

■ Research Question 5. What about the perceptions of an app that classifies whether an apple, banana, or orange is rotten or not?
- Research Question 5-1. Who are the potential users of the app?
- Research Question 5-2. Why did older adults suggest them as potential users?
- Research Question 5-3. Why can older adults trust apps?
- Research Question 5-4. Why can't older adults trust the app?
- Research Question 5-5. What features would older adults like to add to the apps?
- Research Question 5-6. Why do older adults use apps even if they are paid?

By answering our research questions, we contribute to older adults and the community of researchers. First, we proposed a smartphone app that supports older adults in avoiding consuming rotten fruits. Second, we revealed their perceptions of older adults and showed how to evaluate the app that uses an artificial intelligence model. Third, we contribute to the related research community by revealing which of the seven pre-trained backbone networks we used to classify rotten fruits showed the best performance. In order to answer the research questions, our study reviewed the relevant literature and developed and evaluated the performance of the app. For the evaluation of the app, we used an after-scenario questionnaire [32] and conducted semi-structured interviews [33] with older adult participants.

Methods

This study aims to develop and evaluate a smartphone app that enables older adults to take pictures of food items with a smartphone camera and to determine whether the fruit is rotten or not. We first reviewed prior studies that developed and evaluated similar spoilage detection tools. After reviewing the relevant literature, we trained a model that classifies the freshness of three kinds of fruits, apple, banana, and orange, and evaluated the model's performance. Then, we developed a smartphone app that uses the trained model to take images of fruits and classify them into images of fresh and rotten fruits. We recruited 23 older adult participants to evaluate the usability of the app and to determine the perceptions of older adults about the app (see Table 1).

Literature Review

The purpose of the literature review is to discover the limitations of the prior studies that developed and evaluated tools that classify whether food items are rotten or not. To collect prior studies that reported any developed apps determining food freshness by taking a picture of food items, we used a combination of keywords (e.g., rotten, food, collect, and app) in Scopus, IEEE, ACM digital library, PubMed, and EBSCO, respectively. We also used similar meanings for each keyword (e.g., spoiled, corrupt, damaged, ruined, and expired for the similar meaning of rotten) and linked them with "OR" and "AND" as query sentences (see Textbox 2). We exported the article's metadata, such as article title, year, author, DOI, publisher, and keywords, and stored it to Google Spreadsheets. We used the PRISMA flow diagram to manage duplicated articles between databases and to screen review papers [34] (see Figure 1). We found 19 eligible articles, excluding those not meeting the eligibility criteria. After reviewing each article to examine the research questions and objectives of prior studies, we found that no prior studies reported how to support physically healthy older adults to determine the freshness of their diet using readily available equipment such as a smartphone.

Textbox 2. The search query we used in Scopus.

TITLE-ABS-KEY((("spoiled" OR "rotten" OR "corrupt" OR "damaged" OR "ruined" OR "expired") AND ("food" OR "cooking" OR "kitchen" OR "food" OR "food" OR "meals" OR "kitchens" OR "kitchens" OR "food" OR "meals") AND ("pick" OR "pick" OR "take" OR "take" OR "detects" OR "detects" OR "identifies" OR "identifies" OR "recognizes" OR "recognizes") AND ("app" OR "application" OR "system" OR "platform" OR "apps" OR "applications" OR "systems" OR "platforms"))).

Figure 1. PRISMA flow diagram [23] for reviewing prior studies. After deduplicating the papers in each database, we screened review papers and found 19 articles that met the eligibility criteria.

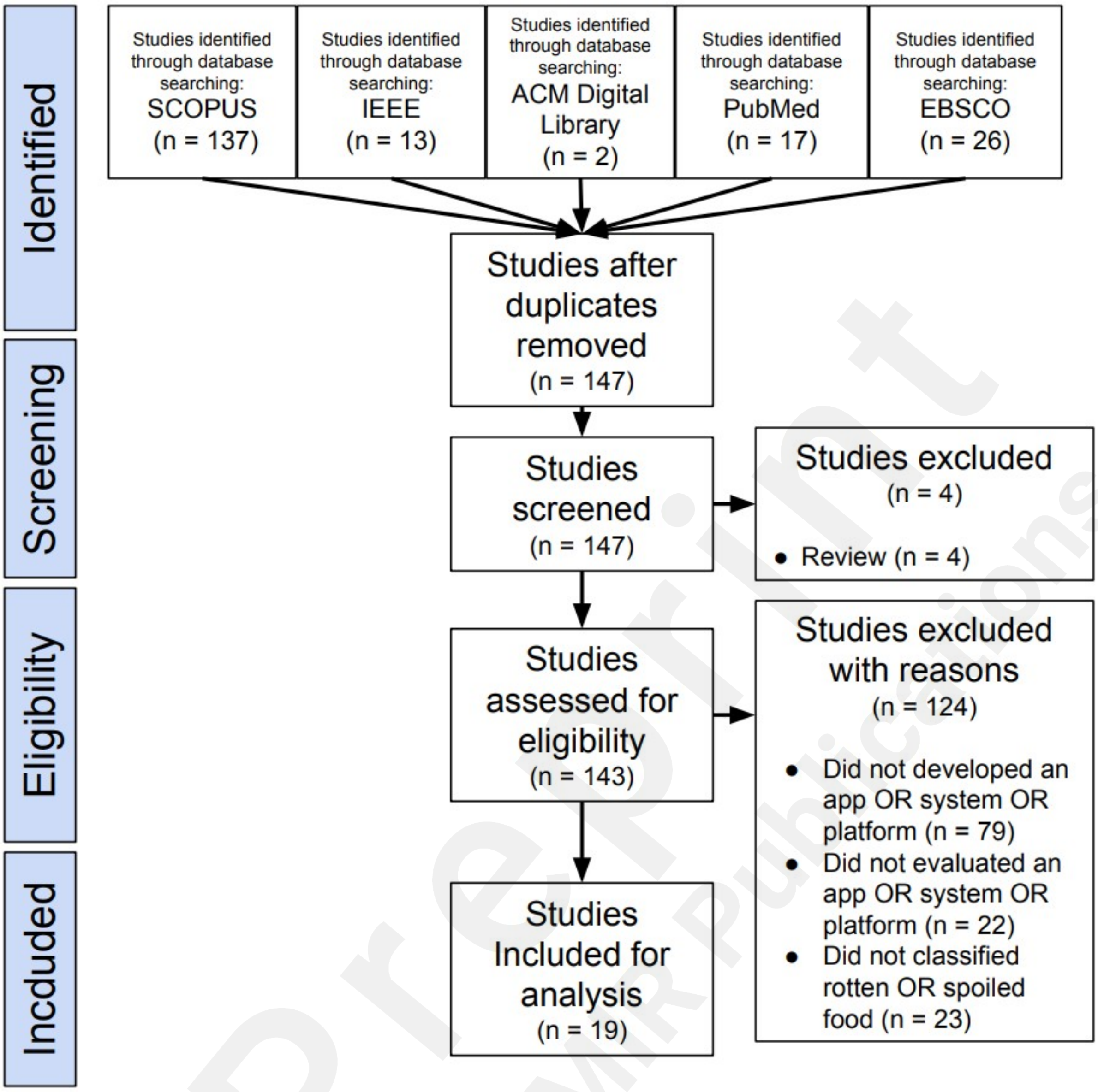
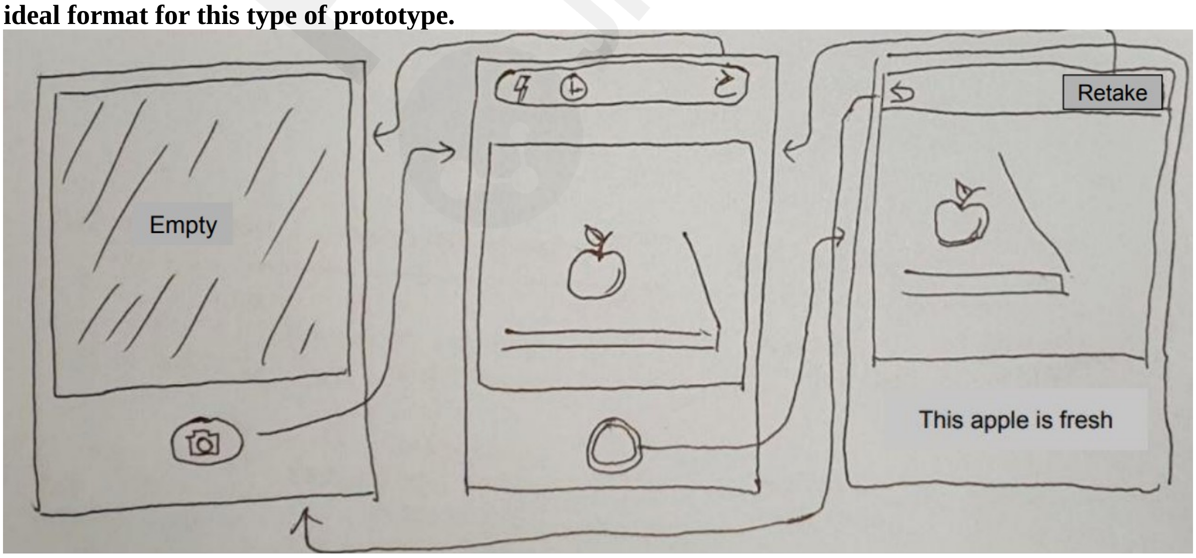


Figure 2. Pictures of apples, bananas, and oranges collected from Kaggle.

Class	Photo	Class	Photo
Fresh apple		Rotten apple	
Fresh banana		Rotten banana	
Fresh orange		Rotten orange	

Figure 3. This figure shows a low-fidelity prototype of the app, intentionally sketched by hand to emphasize the conceptual stage of design. Each box represents the shape of the smartphone running the app. Arrows depict screen transitions triggered by user interaction with specific elements on the screen [35]. Low fidelity prototypes are basic visual representations that do not incorporate high details or functionalities but are essential for rapid iterations and facilitate early discussions among researchers on design concepts, making hand-drawn sketches nan ideal format for this type of prototype.



App Development

The objective of this study is to develop an app that determines whether an apple, banana, or orange is rotten just by taking a picture of the fruit using a smartphone camera. App development and evaluation procedures consist of four steps: (1) collecting images, (2) training classification models, (3) developing an app, and (4) evaluating the models. First, we collected the images required for training the food classification model. We collected pictures of fresh and rotten apples, bananas, and oranges from Kaggle, a platform that provides pre-processed datasets to data scientists. The collected pictures were 2,088 pictures of fresh apples, 1962 pictures of fresh bananas, 1854 pictures of fresh oranges, 2943 pictures of rotten apples, 2754 pictures of rotten bananas, and 1998 pictures of rotten oranges (see Figure 2). We uploaded and stored the collected pictures on the server for classification model training.

Second, we trained food picture classification models. To use only the features of the fruit in the picture for training, we segmented only the pixels of the fruit from the background using Otsu's method [36]. We stored the segmented pictures with the same size as the original pictures. When training a model, we used several pre-trained residual networks (e.g., ResNet 50, ResNet 50V2, ResNet 101, ResNet 101V2, ResNet 152, ResNet 152V2, InceptionResNetV2) for feature extraction, reducing the time for model training and improving model performance [37]. For the fully connected layer, among the parameters used in the single fully connected layer, we set the activation function among sigmoid, ReLU, and tanh. We set the dropout rate from one of 0, 0.1, 0.2, 0.3, 0.4, or 0.5 and set the number of neurons from one of 64, 128, 256, 512, or 1025. We randomly selected 100 combinations of the activation functions, the dropout rate, and the number of neurons. Among the combinations, the layer combination that showed the best performance was consist of dense (neurons=128, activation=sigmoid) layer, dropout (drop rate=0.2) layer, dense (neurons=128, activation = sigmoid) layer, and dropout (drop rate=0) layer.

Third, we developed a smartphone app that utilizes a classification model that classifies fruit photos into fresh and rotten fruit photos. Android Studio [38] is the official integrated development environment for Android apps, and the proportion of smartphone users in their 60s and older is steadily increasing, and the older they are, the more they use Android than iPhones. The target API level 29 of the app is the minimum API level that supports app download from Google Play, and the API level that can be operated on most smartphones was selected. We developed three functions: a function to take a picture using a smartphone camera, a function to input pictures into the classification function, and a function to show the classification result on the app screen. We created a low-fidelity prototype [39] to determine user tasks and three features of the app (see Figure 3). We added a camera function that enables users to take a picture. To add the camera function, we set permissions (e.g., camera, internal storage) for the camera function to take pictures. The picture users took with the app is resized to 256 x 256 pixels to fit the input size of the trained classification model. The resized picture is input to the converted classification model with the .h5 extension. Third, the app takes the output array from the classification model that consisted of probability value and displays one of the following texts: “The apple is rotten," "The apple is fresh," "The banana is rotten," "The banana is fresh," "The orange is rotten," and "The orange is fresh" (see Figures 4 and 5). To perform the above functions, we added several buttons allowing users to interact with the app.

Lastly, we evaluated performances our trained models (e.g., area under curve, error rate). The model evaluation aims to determine the best-performing model among models developed using multiple backbone networks in the model training stage. To fix the metric to be used for model evaluation, we found the metric used to evaluate the classification model in each of the papers found in the related work. A prior study used F1-score, balanced accuracy, error rate, and area under cover to evaluate the classification model [26]. After extracting the above metrics through 10-fold cross-validation, we found a significant difference between each model's performances by using the Kruskal-Wallis test [40]. The Kruskal-Wallis test [40] is a method that can be used when N is 30 or less for three or more classes. We used it to check whether using different backbone networks makes significant differences in model performance.

Figure 4. The four main features of the app. When a user takes a picture of the fruit, the picture is classified with a classification model and returned to the user.

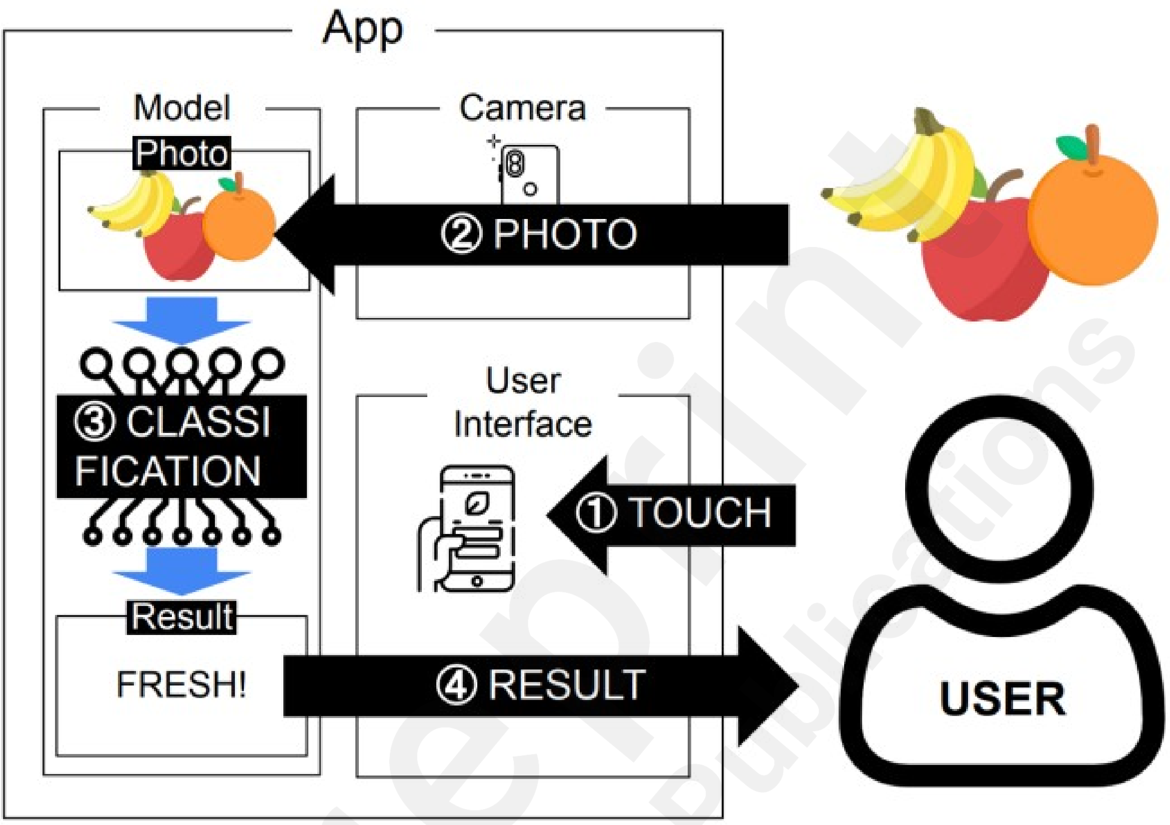
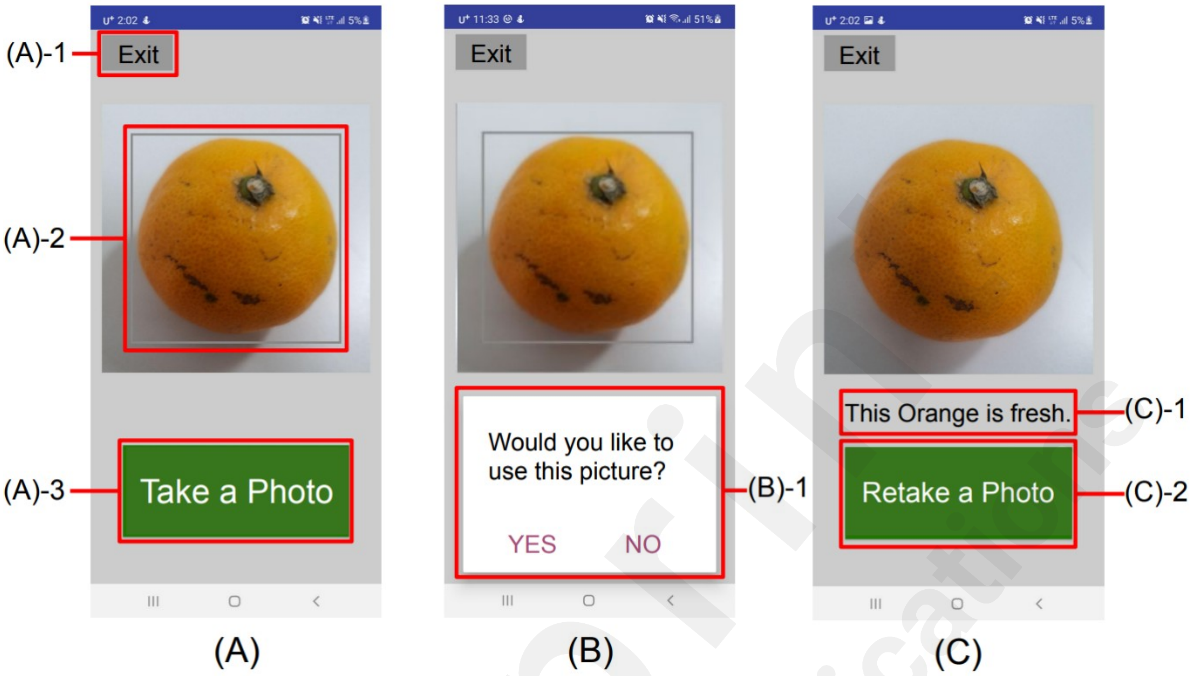


Figure 5. User interface screenshot. (A) An interface where the user takes a picture; (A)-1. A button to exit the app; (A)-2. A screen that shows what the camera is focusing on; (A)-3. A button to take a picture; (B) An interface for reviewing pictures taken by the user and deciding whether to use the pictures taken; (B)-1. A popup that asks the user whether to use a photo; (C) An interface for displaying the results of classifying the freshness of the fruit; (C)-1. A text that indicates the type and freshness of the photographed fruit; (C)-2. A button to return to the home screen of the app so that you can take a picture of another fruit.



Performance Evaluation

We evaluated app's performance to answer research questions 4 and 5, respectively. For evaluation, we performed a performance evaluation of the classification model used in the app, a quantitative evaluation using an after-scenario questionnaire [41], and a qualitative evaluation through semi-structured interviews with older adult participants.

Recruitment

We recruited older adults as participants who are the target users of the app. We set eligibility criteria as follows: (1) 65 years of age or older, (2) those who have used a smartphone with a rear camera for at least one year, (3) those who have taken pictures with a smartphone at least once in the last three months and (4) those who could literacy understand the contents of the questionnaire, (5) those who have lived in Korea for more than five years and can communicate in Korean, and (6) those who have not participated in this study before. However, we excluded participants unwilling to be the research subject or had any special chronic diseases [42]. We recruited participants using three methods: (1) recruiting through acquaintances, (2)

Table 1. Participant demographics.

ID	Age (year)	Gender	Usually take pictures of food often (1: Strongly disagree-5: Strongly agree)	Usually check that food is fresh before eating it (1: Strongly disagree-5: Strongly agree)
P1	65	Female	Not reported	Not reported
P2	70	Male	Not reported	Not reported
P3	66	Female	Not reported	Not reported
P4	66	Female	Not reported	Not reported
P5	65	Male	Not reported	Not reported
P6	69	Male	1	4

P7	73	Female	2	5
P8	73	Female	2	5
P9	65	Female	2	5
P10	65	Male	1	5
P11	74	Male	3	5
P12	69	Female	1	3
P13	69	Male	2	4
P14	65	Male	1	5
P15	69	Male	2	4
P16	76	Male	5	5
P17	69	Male	1	5
P18	76	Male	1	1
P19	67	Female	1	5
P20	72	Male	1	4
P21	68	Female	3	5
P22	70	Male	3	4
P23	65	Male	1	4
P24	66	Female	3	4
P25	68	Male	3	4
P26	66	Female	3	5

recruiting through an institution used by older adults, and (3) recruiting through an online community used by older adults. When recruiting participants through acquaintances, researchers informed people around the researcher [43] about the purpose of the study, the expected time required for the experiment, the eligibility of participants, and the reward. When recruiting through institutions, researchers collected the name, location, phone number, and e-mail of the senior welfare center in Seoul and sent an e-mail requesting to promote the experiment and share a promotional poster. When recruiting experiment participants through an online community, we posted promoting posters by joining social network services such as Open Kakao Talk, Naver Band, and Naver Cafe, which are thought to be used by older adults.

Study Procedure

We evaluated the usability of app through an after-scenario questionnaire and semi-structured interviews. We conducted the experiment by visiting each participant's home. The researcher informed older adult participants of (1) the purpose of the experiment, (2) the purpose of using the app, (3) the expected time required for the experiment, (4) the function of the app, and (5) a brief introduction about the researcher. After informing each participant about collecting information, the researchers asked participants to sign a consent form about participating and recording the interview. After the participant agreed to participate in the experiment, the researcher instructed the experiment participant about three tasks using the app. Each task consists of (1) a task to run the app and review the screen, (2) a task to take a picture of fruit using the app, and (3) a task to review a text indicating whether the picture of fruit the participant took was fresh or not. In order to conduct the experiment in the same environment as possible, the researcher handed the smartphone with the app pre-installed to the participants. To minimize the impact of imaging angles, environments, illumination, cameras, and any other potential factors on the efficiency of classification, the standardized protocol was implemented across all experiments. For instance, each participant was asked to use the Samsung Galaxy Note 10 camera to photograph the fruit for ensuring consistency in device specifications. The photos were taken at a 45-degree angle under sufficiently bright lighting conditions, such as in the kitchen or living room. Furthermore, by having participants align the fruit with the square gray lines shown in Figure 5, we ensured that the orientation and size of the fruit within the images did not affect the classification results. Each participant performed the given task with a fresh apple, a rotten apple, a fresh banana, a rotten banana, a fresh orange, and a rotten orange, respectively. When the participants completed their tasks, the researcher asked them to fill out a questionnaire and interviewed them. The questionnaire consists of questions to remind the usual experiences of participants and memories and questions to answer research questions using the 5-Likert scale (See Table 2). When the interview was over, we stopped recording and paid 10,000 Korean won to the participant in cash. The questionnaire and the consent form were scanned and uploaded to Google Drive along with the interview recording file. The interview recording file was transcribed. Researchers listened to the recording file again and corrected the script.

Table 2. After-scenario questionnaire for study participants using 5-likert scale.

#	The questions to answer the research questions (1: Strongly disagree-5: Strongly agree)
1	I think it was easy to touch the app icon and review the first screen of the app.
2	I feel satisfied with the time it took to touch the app icon and review the app's first screen.
3	I think it was easy to take a picture of the fruit.
4	I am satisfied with the time it took me to take a picture of the fruit.
5	I think it was easy to review the text indicating whether the fruit was fresh.
6	I feel satisfied with the time it took to review the text indicating whether the fruit was fresh or not.
7	I trust the text indicating whether the fruit is fresh or not.
8	Even if the app is paid, I plan to use it.

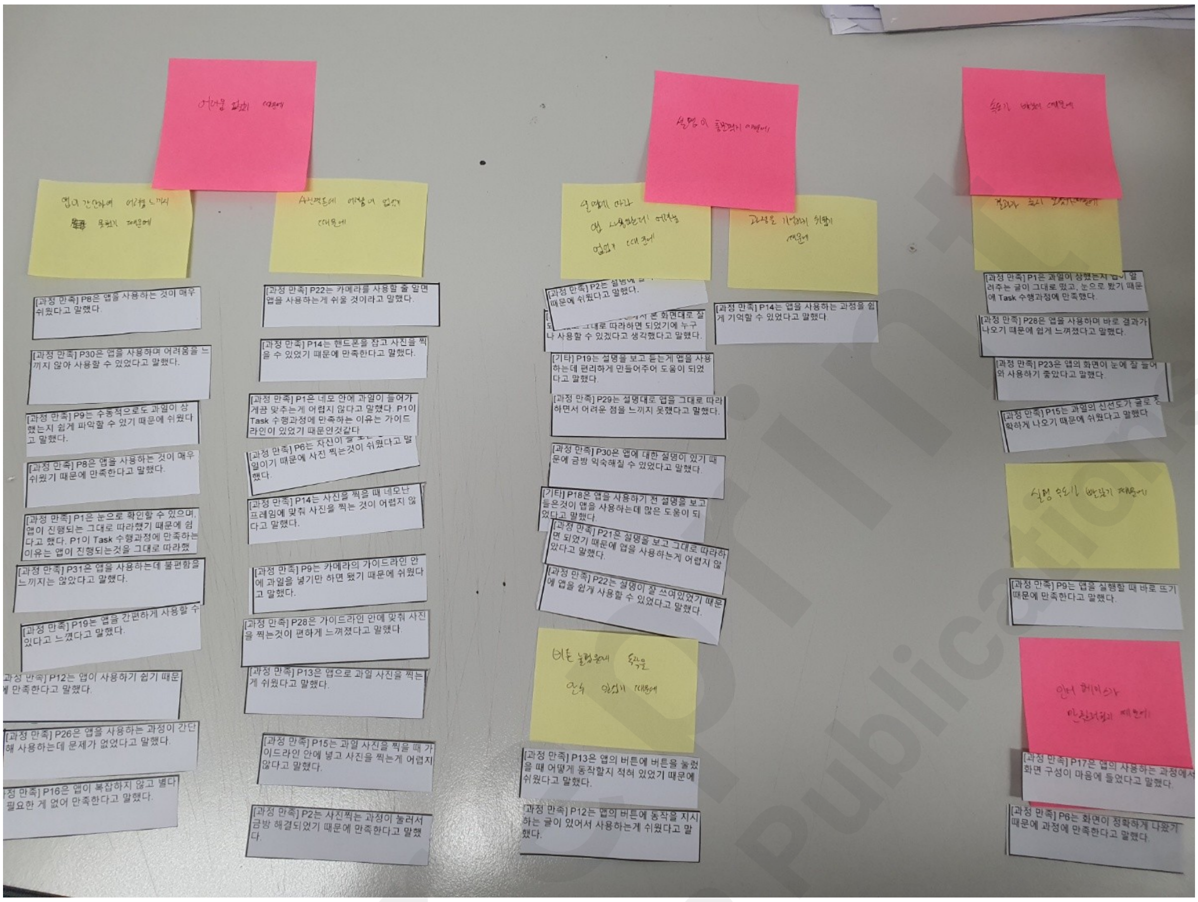
Data Analysis

We quantitatively and qualitatively analyzed participants' responses. We removed every participant's identification information and assigned a new one for each participant (e.g., P1, P2). Then, we calculated the questionnaire response's average and standard deviation for quantitative analysis. For qualitative analysis, we used open-coding methods that highlight meaningful remarks within scripts. We highlighted statements that included important information (e.g., participants’ experiences, preferences) in each script [44]. For each highlighted remark, we assigned a label to summarizes the remarks. We printed all the labels and inductively grouped them to extract important themes that answered our research questions (see Figure 6) [45]. Within qualitative research, affinity diagramming, a technique utilizing sticky notes is a prevalent practice due to its inherent flexibility and tangibility, which facilitates the organization of thoughts and findings in a spatially representative way. The ability to physically manipulate and rearrange data points is a key advantage of affinity diagramming, fostering deeper thematic analysis and the identification of emergent relationships and patterns. This technique also promotes collaborative discussions among researchers by providing a clear visual representation of the data analysis process.

Ethical Considerations

All experimental procedures in this study were approved by the Institutional Review Board at the University of Seoul (IRB ID: 2021-06-001-001). Prior to the experiment, each participant provided informed consent, which included a clause allowing the use of collected data for secondary analyses without additional consent. To protect the privacy of collected data, all participant data were anonymized and stored on a secure drive which only authorized personnel have access to. After completing the interview, all participants received cash compensation of 10,000 South Korean won (approximately US $8) for their participation.

Figure 6. This figure depicts a qualitative data analysis process, a vital step in numerous research methodologies. The white notes represent codes written by the researcher to excerpts from interview transcripts. These codes highlight key ideas or concepts within the data. The yellow notes signify emergent themes identified through an initial coding stage. Here, similar or related codes are grouped together to synthesize broader patterns within the data. The red notes denote overarching themes or categories derived from a subsequent grouping of the yellow notes. This final stage reflects a higher level of data abstractions, moving from specific codes to more general thematic constructs.



Results

The results of our study are classified into (1) performance evaluation results of the trained model during app development, (2) quantitative analysis results of responses collected through the survey, and (3) qualitative analysis results of responses collected through interviews.

Model Performance

We trained each classification model using seven residual networks as a backbone and compared the performance using 10-fold cross-validation to review whether there was a significant performance difference. The ResNet101 showed the highest performance on average (see Table 3). In this study, the optimal architecture for the fully connected layers was identified as a sequence containing a dense layer with 128 neurons and sigmoid activation, a dropout layer with a drop rate of 0.2, followed by another dense layer with 128 neurons also using sigmoid activation. The final layer in the sequence is a dense layer without dropout. The learning rate was set to 0.001. The training process was configured with 1,000 epochs, incorporating an early stopping mechanism with a patience parameter of 20. Whether the model trained using ResNet101 and the rest of the backbone network showed a significant performance difference was verified using the Kruskal-Wallis test [46]. As a result, ResNet101 showed a significant performance difference from ResNet50, ResNet50V2, ResNet101V2, and InceptionResNetV2, but did not show a significant difference between ResNet152 and ResNet152V2. Therefore, although the trained model using ResNet101

showed
the highest performance among the seven backbone networks, there was no significant performance difference when compared with ResNet152 and ResNet152V2.

Table 3. After training the model using each backbone network with 10-fold cross-validation, the area under curve, error rate, balanced accuracy, and f1-score of ResNet101 in bold showed the highest performance.

#	Backbone	Area Under Cover	Error Rate	Balanced Accuracy	F1-score
1	ResNet50	0.9533	0.3589	0.7523	0.7615
2	ResNet50V2	0.9456	0.3591	0.7409	0.7495
3	ResNet101	**0.9663**	**0.3216**	**0.7949**	**0.8003**
4	ResNet101V2	0.9467	0.3533	0.7403	0.7494
5	ResNet152	0.9607	0.3475	0.7783	0.7833
6	ResNet152V2	0.9606	0.3250	0.7806	0.7884
7	InceptionResNetV2	0.9210	0.4097	0.6821	0.6932

Survey Results

Table 4. Survey results that show the perceptions of older adults about the app. Average and standard deviation values are expressed as Mean (SD).

#	Survey Questions (1: Strongly disagree, 5: Strongly agree)	Mean (SD)
1	Do you agree that running the app and reviewing its first screen was easy?	4.58 (0.70)
2	Do you agree that you were satisfied with the time it took to run the app and review its first screen?	4.77 (0.51)
3	Do you agree that taking pictures of fruit was easy?	4.81 (0.49)
4	Do you agree that you were satisfied with the time it took to take a picture of the fruit?	4.81 (0.40)
5	Do you agree that reviewing the text indicates whether the fruit is fresh was easy?	4.73 (0.67)
6	Do you agree that you were satisfied with the time taken from taking a picture of the fruit to reviewing the text indicating whether the fruit is fresh?	4.88 (0.33)
7	Do you agree that you trust the result displayed on the app?	4.38 (0.90)
8	Do you agree that you intend to use the app even if you have to pay for it?	2.73 (1.28)

We obtained the average and standard deviation of the demographic information and the responses to each survey question. Out of a total of 32 responses, six participants (identification numbers P3, P4, P5, P7, P10, and P11) did not meet the criteria for participation, so their responses were excluded. According to the demographic information shown in Table 1, the average age of the 26 experiment participants was 68.69 years (SD 3.47), of which 15 were males (57.69%), and 11 were females (42.31%). The participants generally had a positive perception of the app (see Table 4). They generally agreed that it was easy to run the app and review the first screen of the app. Also, participants generally agreed that they were satisfied with the time it took to run the app and review the app's first screen, thought that taking pictures of fruit was easy, satisfied with the time it took to take a picture of the fruit, thought that reviewing the text indicates whether the fruit is fresh was easy, satisfied with the time taken from taking a picture of the fruit to reviewing the text indicating whether the fruit is fresh, trust the result displayed on the app. However, they disagreed that they intend to use the app even if it is a paid app. According to the results, the participants thought they could review the freshness of fruit efficiently with the app. However, although they could trust the app, they showed reluctance to pay to use the app.

Interview Results

We analyzed the interview results qualitatively to answer the research questions: why older adults are satisfied with the process of using the app, why older adults are not satisfied with the process of using the app, why older adults are satisfied with the time taken to use the app, why older adults satisfied while using the app, why older adults felt dissatisfied while using the app, what older adults wished about the app, potential users of the app suggested by older adults, why older adults suggested the potential users, why older adults trust the app, why older adults do not trust the app, additional features that older adults suggested, and why older adults use the apps even if they need to pay. Since no older adults responded that they were dissatisfied with the time taken to use the app, we excluded the answer to the research question from the results.

The reasons why older adults are satisfied or dissatisfied with the process of using the app

Participants stated that there are several reasons why they are satisfied with the process of using the app. For example, ten participants reported that the app was simple and easy to use: “I don't have to do something in several steps, I just take pictures” (P10). Similarly, seven test participants responded that they had no difficulty taking pictures: “It wasn't difficult for me to take pictures using the app” (P22). Six test participants answered that it was not difficult to use the app according to the sufficient descriptions: “The description of the app was very helpful. Without this explanation, I would have taken the wrong picture, and I don't think I would get the desired result” (P12). Four participants responded that the app works fast, so they immediately saw a text indicating the freshness of the fruit on the app: “As soon as I took a picture, the text was immediately visible, so I could check whether it was fresh or not, which was nice” (P22). Two test participants said they were satisfied with the interface: “I think I can give it almost 90 out of 100 points for touching and reviewing the screen of the app. The screen composition is almost 90 points” (P11).

However, some participants still found it difficult to take pictures or check freshness. Two participants reported that taking pictures using the app was difficult: “It would be much better if I could just take pictures, whether from close or far away. But when I tried to fit the object inside the square, my hand was shaking, which made it difficult to take the photo (P12). Two participants reported that they could not quickly check the freshness text: “The speed at which I can check whether the fruit is fresh or not will still be around 3 out of 10. I couldn't check it right away” (P3).

The reasons why older adults are satisfied with the time it takes to use the app

Participants were generally satisfied with the time it took to use the app. Thirteen participants answered that it did not take long to use the app: “When I touched the app, it didn't feel like it took that long, such as buffering, and the screen popped up immediately” (P23). Two participants answered that they felt it was easy to use the app: “I felt satisfied because I understood it quickly” (P7). One participant answered that she was satisfied with using the app because it took a long time: “I liked being able to use the app at my own pace rather than using it quickly” (P3).

The reasons why older adults are satisfied or dissatisfied with using the app

Participants answered that they were satisfied with the app because it was visually pleasing and because it was simple. Sixteen participants reported that the interface of the app was visually satisfactory: “It was easier because the font size was okay and the freshness was simply indicated”

(P14). Eight participants reported that they had no difficulty taking pictures using the app: “The app is so easy to use because I can take a picture right away. When taking pictures of distant objects with a general camera, I need to adjust the distance and adjust the direction, but with this app, it was easy” (P15). Six test participants responded that the process was simple and easy to use: “This app was uncomplicated and easy to use” (P15). Two test participants said that the app is easy to use because it does not require any authentication to use: “For example, it doesn't require authentication or anything like that, just taking a picture” (P10). Two test participants said they liked being able to check freshness using the app: “I think that using the app is easier than tasting or smelling or anything like that. In order to check the smell or taste, I have to come in direct contact with the food now, so there is such an inconvenience” (P14). Two study participants said that the app could provide health-related information: “The most important thing is to check things related to my health” (P2). Two participants responded that they enjoyed using the app: “With my children, I check whether the fruit is rotten or not, and there are things like that. That could be fun” (P15).

However, some participants reported that they had difficulty using the camera or that the app was too simplistic. Seven participants responded that they felt troublesome while using the app: “When we look at the fruit with our own eyes, we clearly identify whether it is fresh. Other methods make me inconvenience” (P9). Four participants responded that the interface is still small: “It would be better if the camera screen were bigger” (P17). Two participants said that using the camera was uncomfortable: “The app was similar to the camera, but the camera app is better because it is good to focus on an object” (P13). Two participants said the app's design was too simple: “I think the app needs to be a little more sophisticated. The elements are so angular and seem like a little basic app” (P16). Two test participants said the app's functionality was too simple: “The app is too simple. I have no intention of using the app because of the few features” (P5). One participant said that using the app might appear to question the freshness of the food items: “I think it would be a bit strange to take a picture while having a meal together. But if the app has become a bit more popular, I think it's okay to try it once.” (P22).

What older adults want from using the app

Participants wanted the app to inform them of fruit freshness in various ways, and they also wanted the app to be improved detection accuracy. Ten study participants said they wanted to learn more about using the app: “It would be nice to check the freshness of not only fruits but also the kinds of herbs and various food items (P15).” Seven participants said they wanted the app to be easier to use: “If the fruit pictured here is rotten, I think the result should be displayed in red, or if it is fresh, it should be displayed in blue. It's fine now, but wouldn't it be better if the app guided me with red, blue, and yellow colors (P25)?” Three test participants said they wanted the app to give accurate freshness: “I think the results are inaccurate. I will use it if the accuracy is higher (P9).” Two test participants said they wanted to check freshness in a variety of ways: “The app only checks the freshness by the shape of the fruit. Can we add a function using a smell or something like a taste (P20)?” One experiment participant said that he would like to see an additional way to earn points as he uses the app: “It would be nice if there were merits, such as earning points the more I use the app (P2).”

In addition, participants suggested some features for the app. Participants wanted to make it easier to take pictures or to get more information about the fruit. Three participants said that they would like the app to automatically focus on the fruit when they take a picture of a fruit: “Rather than focusing the camera on an object, it will be convenient to know the result just by being on the screen, no matter how the camera captures the fruit (P5).” Two test participants said they would like to add a feature that gives more information about the fruits they have taken: “So if I just take a picture of the fruit, the app has to tell me all the information about the fruit (P5).”

Potential users of the app

Participants answered that they would be able to recommend the app to their acquaintances, homemakers, and even young people. Four participants suggested that their acquaintances could use the app: “I'll try to share it with the church's female teachers and priests of my age (P17).” One participant suggested that she could recommend the app to homemakers: “I think homemakers will use it a lot (P23).” Four participants suggested that they could recommend the app to people over the age of 50, including older adults: “I think people who are as old as us or older can try it (P12).” Two participants suggested that they could recommend the app to younger people: “In my opinion, young people in their 20s and 30s have no experience checking the freshness, so that the app may be widespread (P21).” Three participants suggested that using an app to check freshness at a fruit shop would give customers peace of mind: “Individuals, of course, need to check the freshness at home, but a fruit store asks customers to check the freshness of the fruit using an app, and if the fruit is fresh, then customers can buy with confidence (P20).” One participant suggested that she could recommend the app to health-conscious people: “I can recommend an app to anyone sensitive or unusually picky about health and food items (P4).” One participant said that he did not intend to recommend the app to others: “I do not intend even to recommend the app to others (P10).”

Participants said that potential users of the app would quickly learn how to use it. Seven participants said the app was simple and would make it easier for potential users to use it: “Rather than saying that this is easy to learn, isn't it that everyone can do it right away? Because the app is very simple and easy. I think this can be done whenever a person feels it is necessary without the need to learn anything (P20).” Three participants said that potential users would be able to use the app to purchase fresh food items: “Since homemakers buy the most ingredients at the mart, I can recommend it to housewives (P23).” Two participants said that potential users would be able to use the app to tell if the food item was visually fresh: “When they say they are unsure if the fruit is fresh by looking at it, wouldn't it be possible to check it through the app (P19)?” One participant said that if there is a good app, it should be shared with potential users: “The good thing is that we all have to share (P16).” One participant said that a potential participant would be interested in trying the app out of curiosity: “I'll probably try it at a mart or a fruit store mainly out of curiosity (P21).”

Why older adults trust or distrust the app

Participants were less skeptical of the app and tended to believe it, and only a small fraction of participants said they would compare it with their own thoughts. Nine participants answered that they could trust the app because it was just an app to tell them about freshness: “I didn't think about why, and if I don't trust my cell phone, what do I believe? I just believed it (P7).” Two test participants said that they could trust the app if they use it frequently: “If I use the app once or twice and the results are correct, then I should trust the app (P15).” Two test participants responded that the results were the same as they thought: “When I look at the fruit, if it looks like the fruit is rotten and matches the result, then I can trust the app (P16).”

However, some participants say they trust their senses more than the app. Seven participants said they trusted their senses more than the app: “Wouldn't it be more accurate to check with my own eyes rather than the app (P19)?” The three participants answered that their thoughts on the freshness of the fruit and the results were different: “In my opinion, the fruit is not fresh, but the app says the fruit is fresh (P9).” Six participants answered that it was because they had not used the app much: “If the results are certain when I use the app, I'll believe it from now on, but this is the first time I've used it. (P15).”

Why do older adults use or don't use the app if they need to pay

Most of the participants said they would not use paid apps that require money to be used because they are reluctant to pay to use them. Eight participants said that they did not feel the need to use a paid app: “I don't think I need to use an app that requires money (P20).” Four participants responded that they found it difficult to use the app: “It is inconvenient to use such an app; I do not know whether it is paid or free, and I do not need it too (P18).” Three study participants said they prefer free apps: “So, first of all, it's better to be free (P10).” Two participants answered that using paid apps requires money: “Older adults prefer to save money rather than not believe the app (P7).” Eight participants responded that if they needed the app, they would pay to use it depending on the situation: “If I thought I really needed the app, I would use it often (P22).”

Discussion

The results mentioned above showed the behaviors and perceptions of older adult participants when using the app. The survey responses revealed older adults' positive perceptions of the app's ease of use and their satisfaction with the time taken to complete tasks. However, the survey also showed a low willingness to pay for the service among older adults. Interviews provided further insights, revealing user appreciation for the app’s usability, rapid results generation, and straightforward interface. Conversely, some participants expressed a desire for more features, while others raised concerns regarding trust in the app. In the following section, we discuss findings based on the results, limitations of our study, and future work.

Factors affecting satisfaction when using the app

Some participants mentioned that they were satisfied, even though it took a long time to review the freshness of rotten fruits using a smartphone app. In general, it is thought that the shorter the time it takes for users, the more satisfied they will be, but rather, she said that the longer it takes, the more she feels satisfaction. That is, when older adults use mobile health apps for health management purposes, the factors that have the greatest influence on older adults may be different with time. According to a study that found the dissatisfaction of older adults who watch YouTube using smartphones, it is the data plan that older adults feel the most dissatisfied with [47]. This finding is very similar to our results. When older adults use mobile health apps for health management purposes, the most unsatisfactory thing for them may be that they need to pay costs or equivalents. We found that some older adults enjoy the process of using apps rather than reaching their own goal. According to a study that revealed the reasons why older people use YouTube, they use YouTube to gain knowledge about political and social issues, travel information, food recipes, and health information [47]. In other words, it can be seen that when older adults use a specific app, they can also enjoy the process of achieving that purpose. Harris et al. suggest that perceived usefulness, ease of use, and enjoyment are significant motivators for older adults to adopt new technologies [48]. Consequently, the enjoyment derived from using smartphone applications may potentially mitigate the initial hurdles faced by this group in technology adoption. Additionally, clear instruction materials and reduced costs are identified as further facilitators for older adult engagement with deep learning and smartphone-based technologies [48].

Potential users of the app

Some participants responded that the app for classifying fruit freshness would be necessary for young people who lack experience in distinguishing rotten fruits instead of older adults. Young people who lack experience in distinguishing rotten fruits by sense may need the app, and they may consume rotten food items due to the lack of experience in checking freshness even if their cognitive function is normal. According to a study that revealed some kinds of bacteria that cause food poisoning are most detected on the hands, coliform was detected the most in the hands of elementary school students [49]. Based on this, it seems that the age groups most likely to experience health problems due to food poisoning are students rather than older adults so they may be potential users of the app.

Factors Affecting Interview Participants' Confidence in the App

Some experiment participants answered that they trusted the app result because it was an app running on a smartphone, unlike our thought that the older adult users needed something to convince them to trust the app. We discovered that some people might not need a reason to believe and use something. A study examining the effect of trust in technology on the adoption of technology before revealing why older adults trust and use the app without any rationale shows that the app's background factors greatly influence the adoption of technology [50]. Likewise, we assume that some older adults who use the app without evidence not just trust the app but also another technology that they think will work behind the smartphone's system.

Limitations and future work

We developed an app that detect a rotten fruit for the health management of older adults and investigated the experiences of older adults from various aspects. However, future work is still needed to gain deeper insight into the topics discussed. First, we made a smartphone app that determines whether the fruit is fresh or not when older adults picture it, but the app does not include a function to distinguish the freshness of food items other than the three kinds of fruit. According to the experiment results, eight participants wanted to know the freshness of food items other than the three types of fruit. It might be important to determine the freshness of a wider variety of food items, such as vegetables, herbs, and meat, to contribute to preventing older adults from experiencing health problems from eating rotten food items. However, to determine the freshness of food items other than the three types of fruits, a large number of images is required, which requires a lot of time and resources. According to a previous study that proposed a visual-based method for detecting rotten food items, rotten food items had common visual characteristics [51]. Using common visual characteristics of rotten food items might enable the determination of the freshness of more diverse food items without collecting corresponding food image data.

Second, we used seven networks as backbone networks to create a model that can distinguish the freshness of three kinds of fruit. We selected ResNet 101 with the highest classification performance among backbone networks. However, we did not use several other backbone networks. Using more diverse backbone networks, including the recently proposed backbone network, might improve the performance of the model. Recently proposed models in a classification problem using ImageNet showed more than 10% higher accuracy than the backbone network used in our study [52-53]. The performance of classifying rotten food images might be greatly improved using the recently proposed network.

Third, we analyzed the collected interview scripts using open coding, but two or more researchers did not participate in this step. Participation of more than two open coders is required to enrich the quality of the results and reduce the bias that may occur while a single coder is performing the analysis.

As for future work, first, in order to help older adults use the app for determining the freshness of various food items and not eat rotten food items, researchers would need to add a function that distinguishes the freshness of food items other than the three types of fruits. Second, to enable older adults using the app to more accurately check the freshness of food items and not eat rotten food items, researchers may adopt recently developed networks that show high performance in image classification as a backbone network. Researchers may use a pre-trained image processing transformer [54], by finetuning it with the image data we collected. We may also extend the possible food categories by using generalized zero-shot learning [55]. Third, for app improvement, data collected from a questionnaire and interviews should be analyzed by two or more coders to guarantee the reliability of the findings of this study.

Conclusions

The ultimate goal of this study was to help older adults avoid any rotten food items and not suffer from health problems. We established research questions and goals based on the limitations of the prior studies where researchers created and evaluated a tool for detecting rotten food items. To achieve the goals, we obtained the highest-performing classification model among various backbone networks by training a model to determine whether the targeted fruit was rotten. The trained model was used for developing a smartphone app. The findings of this study with older adult participants revealed that the usability of the app and the older adult's perceptions of the app were positive, respectively, but they tended to feel reluctant to use the app if they needed to pay for it. We also found how to design and evaluate an app with AI models targeting older adults by uncovering their perceptions of the app. Our study contributes to the research community by revealing which of the seven pre-trained backbone networks showed the highest performance on the ImageNet classification problem for determining if the targeted fruit was rotten. We hope our proposed app enable older adults to identify rotten food items efficiently for maintaining their health.

Data Availability

The data sets generated and analyzed during this study are available from the corresponding author on reasonable request.

Abbreviations

SD: Standard Deviation

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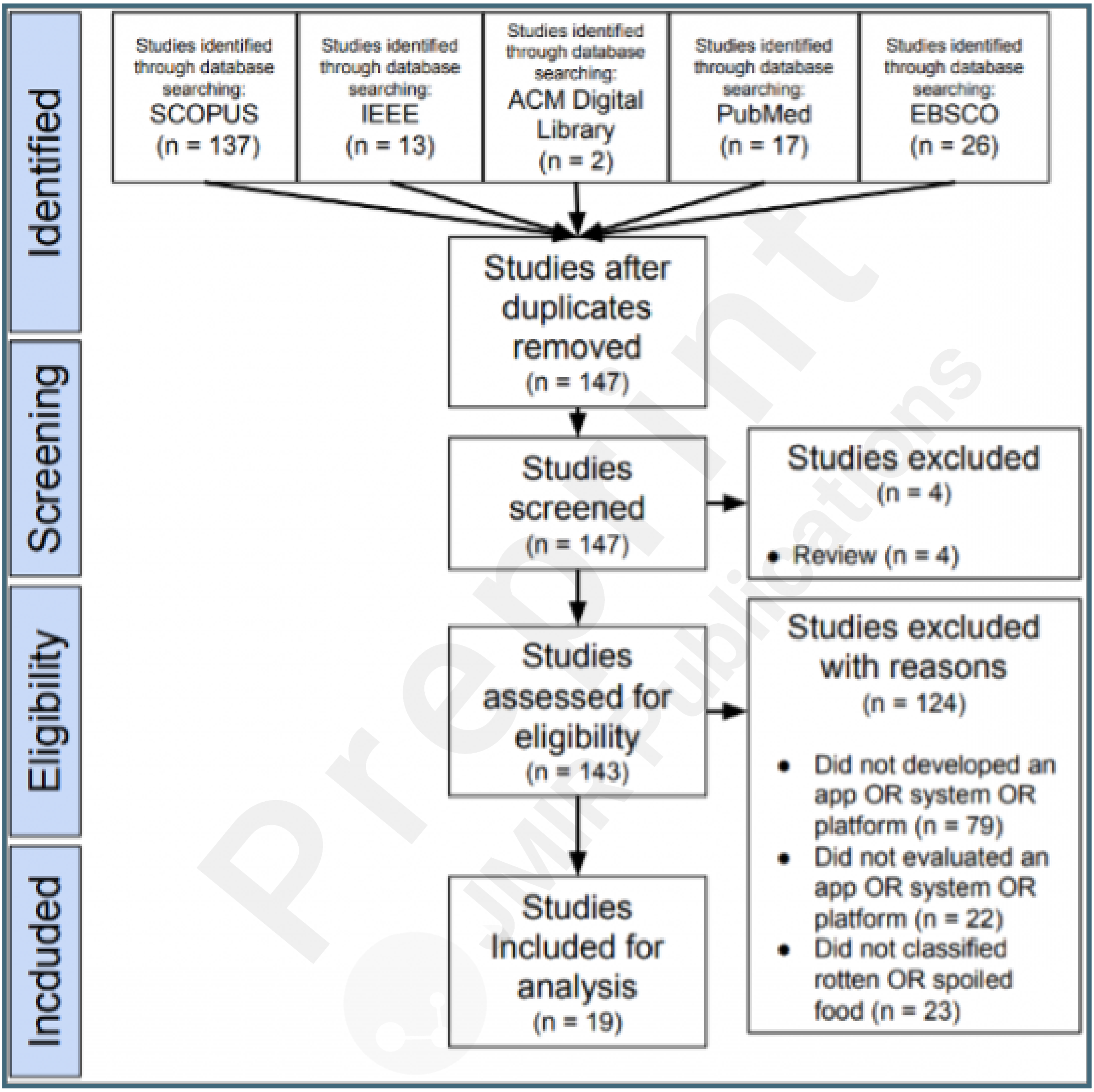
Supplementary Files

Untitled.
URL: http://asset.jmir.pub/assets/33d8c00aa3d40549037ca537b56abdb4.docx

Untitled.
URL: http://asset.jmir.pub/assets/e69b13cb5b61c60202e99c8130c30934.docx

Figures

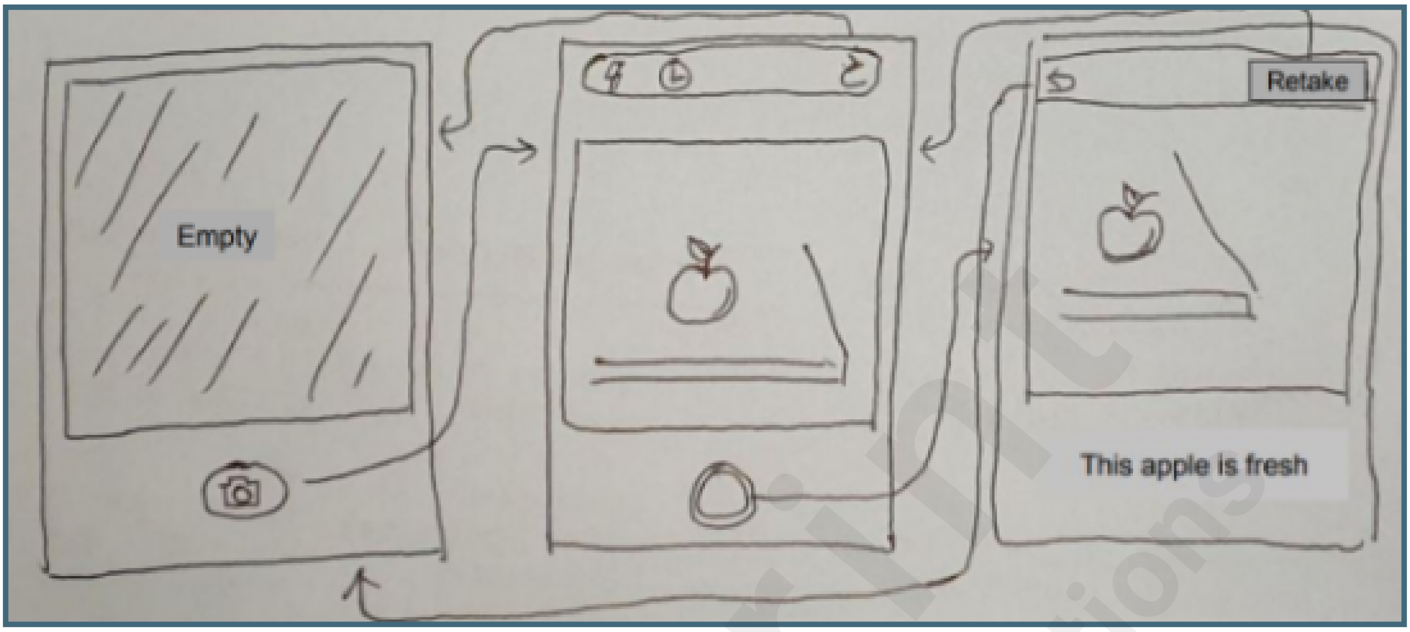
PRISMA flow diagram for reviewing prior studies. After deduplicating the papers in each database, we screened review papers and found 19 articles that met the eligibility criteria.



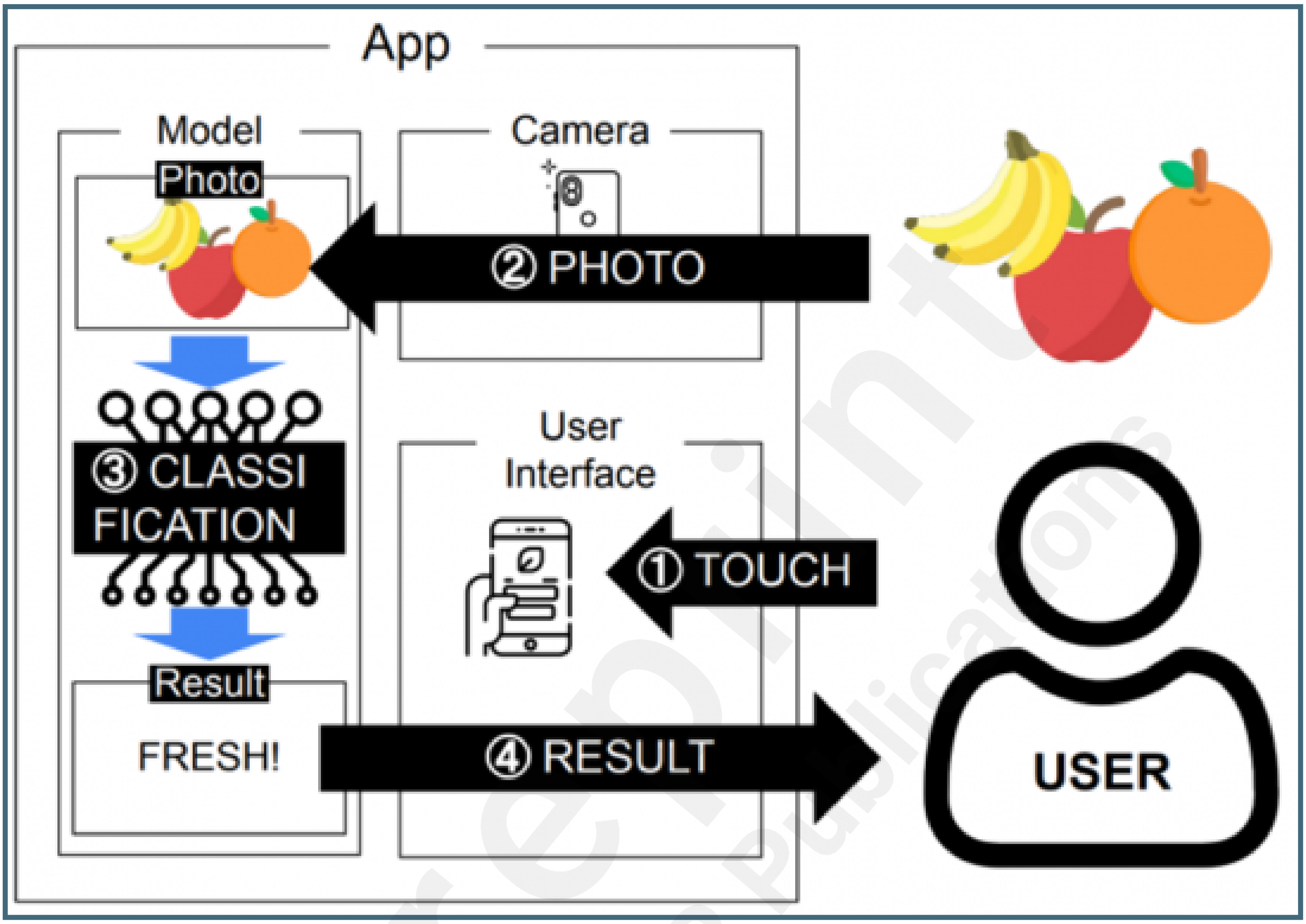
Pictures of apples, bananas, and oranges collected from Kaggle.

Class	Photo	Class	Photo
Fresh apple		Rotten apple	
Fresh banana		Rotten banana	
Fresh orange		Rotten orange	

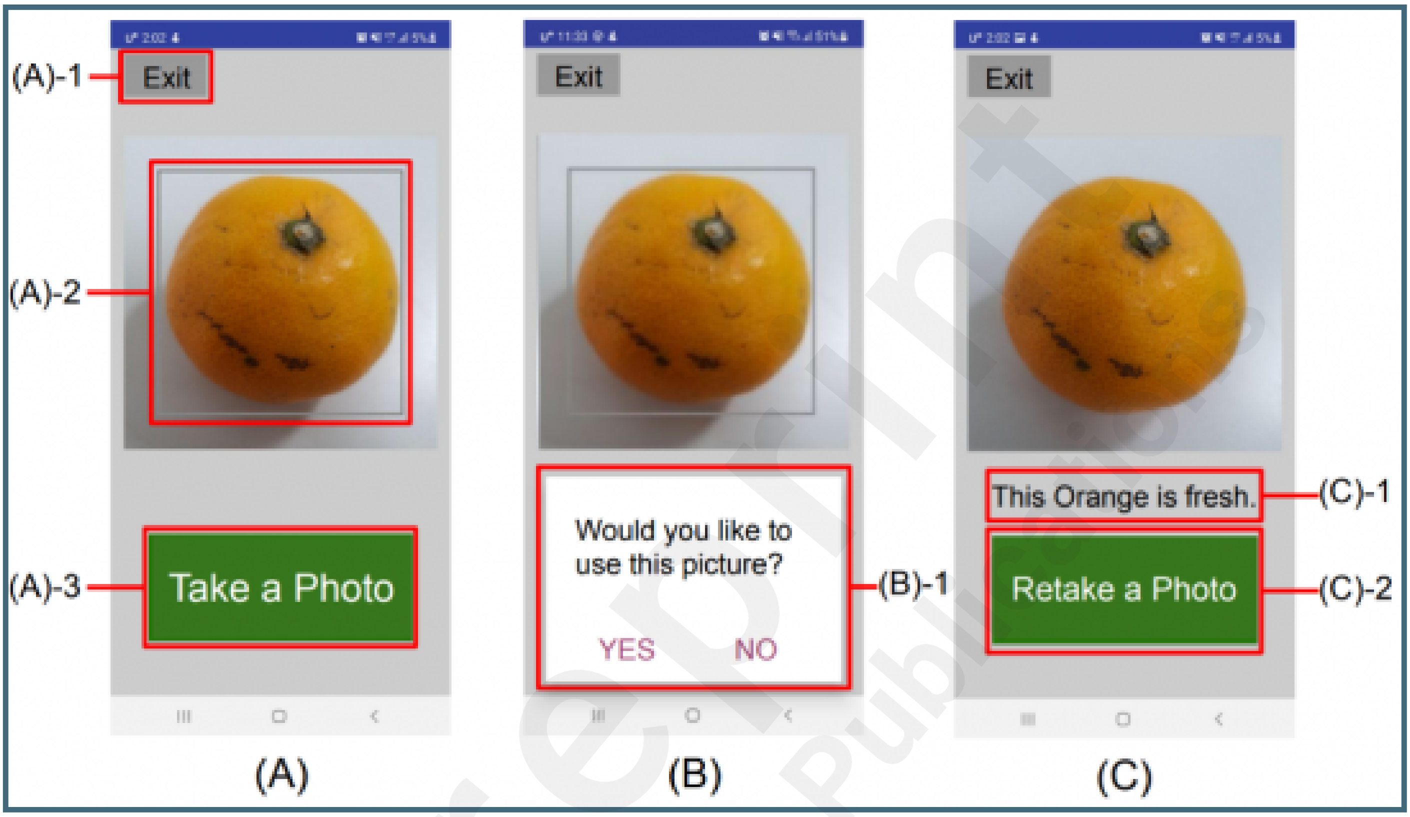
Low-fidelity prototype of the app. Each box represents the shape of the smartphone running the app, and the arrow represents the app screen transition when the corresponding element is touched.



The four main features of the app. When a user takes a picture of the fruit, the picture is classified with a classification model and returned to the user.



User interface screenshot. (A) An interface where the user takes a picture; (A)-1. A button to exit the app; (A)-2. A screen that shows what the camera is focusing on; (A)-3. A button to take a picture; (B) An interface for reviewing pictures taken by the user and deciding whether to use the pictures taken; (B)-1. A popup that asks the user whether to use a photo; (C) An interface for displaying the results of classifying the freshness of the fruit; (C)-1. A text that indicates the type and freshness of the photographed fruit; (C)-2. A button to return to the home screen of the app so that you can take a picture of another fruit.



A picture that shows the process of qualitative data analysis. The white notes are the code the researcher wrote for each interview script, and the yellow notes are the theme found when the researcher first grouped the white notes. The red notes are a larger theme that the researcher found when grouping the yellow notes into several categories.